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# Uncertainty analysis of user behaviour and physical parameters in residential building performance simulation

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ABSTRACT

The objective of this study is to analyse uncertainties in building simulation through a probabilistic approach. The EnergyPlus computer programme was used to assess a model of a low-income house located in Florianópolis, southern Brazil. Uncertainties of the user behaviour and physical parameters were obtained through literature review and field survey, respectively. The Latin hypercube was used to create a sample of uncertainties to analyse the thermal performance and energy consumption of the house. A sensitivity analysis using the Standardised Regression Coefficients was performed to obtain the most important parameters in the thermal performance and energy consumption. The results showed that the relative deviation with 95% confidence ranges from 6.6% to 21.5% on the degree-hour for heating and cooling, and from 19.5% to 43.5% on the energy consumption for heating and cooling, respectively. These percentage values are the uncertainties found in each analysis. The specific heat and thickness of materials, solar absorptances, ground temperatures, and the albedo (physical uncertainties) and the occupancy schedules, the equipment power and the number of occupants (user behaviour uncertainties) were important parameters in the analysis. Thus, such parameters must be measured or estimated by more precise methods as they most influence the simulation results.



## 1. Introduction

Building performance simulation is a well-known technique in the engineering field, and through it, many advantages in creating optimized designs can be achieved, and strategies for energy efficiency and renewable energy can be implemented [1]. However, a large number of parameters is required along with multidisciplinary knowledge of the user [2], which indicates that computer simulation programmes should be used with care.

There may be many uncertainties in a building performance simulation, including physical, scenario, design, and algorithms uncertainties [3]. These uncertainties take into account the measuring methods of the thermal properties of materials, the operation of the building, the weather files, and heat and mass transfer algorithms.

Thus, it is important to use techniques to quantify these uncertainties and to assess the impact of each parameter on the variable that is analysed via computer simulation.

According to De Wit and Augenbroe [4], the evaluation of the thermal performance of buildings still in design phase involves the consideration of uncertainties, and any result presented without confidence interval has no scientific value [5]. The uncertainty analysis helps to determine such interval and achieve valid and more realistic results.

The consideration of uncertainties in models not only implies variations on specific input parameters but also changes all the design of an experiment. Thus, a probabilistic approach is used instead of a common deterministic approach, which considers the intervals in output variables caused by uncertainty in the input parameters [6].

An uncertainty analysis is linked to a sensitivity analysis, which aims to determine the parameters that most contribute to the variability of results [7], i.e., the most important parameters of the experiment.

Summarizing, the uncertainty analysis refers to the probability distribution of the dependent variables (output), and the sensitivity analysis refers to the rank of the most important parameters (input) that generated the variation [3].

Breesch and Janssens [8] analysed the uncertainty in the prediction of thermal comfort by night natural ventilation strategies in an office building. According to the ATG thermal comfort method (adaptative temperature limit indicator, in Dutch) and the Latin hypercube sampling, the probability of good results was higher in cases with cross ventilation than in cases with unilateral

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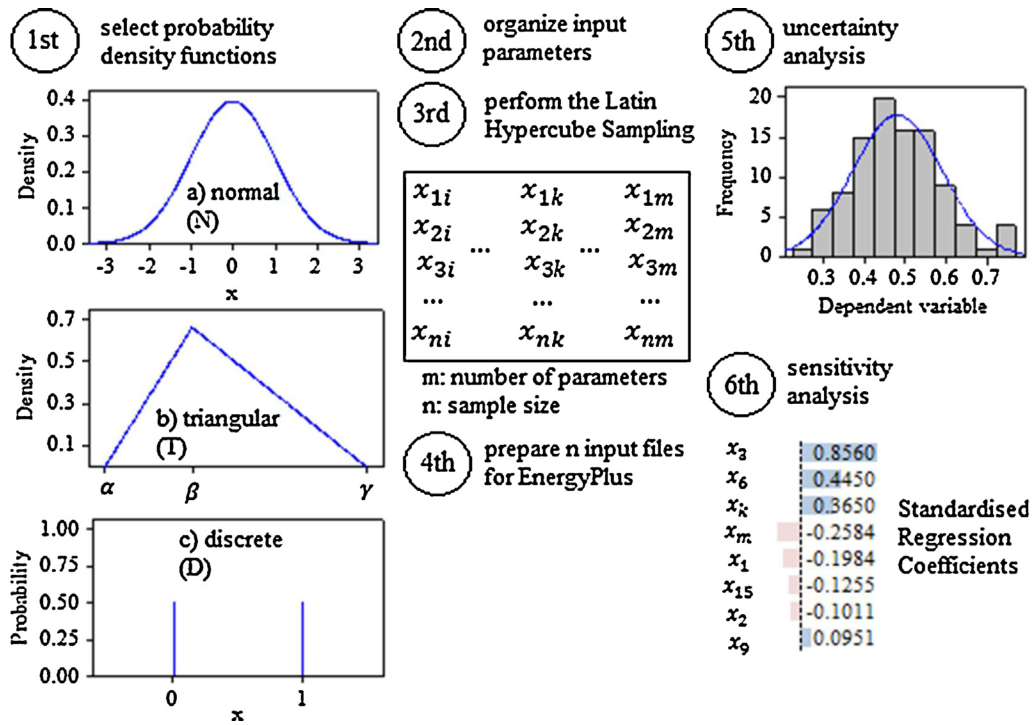



**Fig. 1.** Summary of the method.

ventilation, for the same wind direction. The sensitivity analysis with Standardised Regression Coefficients has pointed out, among the 72 parameters analysed, the internal loads as the most important parameters on the variability of the results.

Heo et al. [9] proposed a method for calibration of computer models for analysis of thermal performance from Bayesian approach, considering uncertainties in the input parameters, the simulation algorithms and measurement methods. The model used to illustrate the method was a commercial building with water heating system. The sensitivity analysis method by the Morris Elementary Effects [10] pointed out as important parameters those related to the opening of windows, internal set point temperature, air infiltration rates, discharge coefficient of the windows and equipment power in the internal zones.

Hopfe and Hensen [3] analysed two types of uncertainties in a computational model (physical and design uncertainties), in which the dependent variable was the energy consumption for air conditioning. The Latin hypercube sampling method with 200 random simulations was used for each type of uncertainty. The most important parameters were the infiltration rates in physical uncertainty and the floor plan area in design uncertainty. Therefore, in order to reduce the uncertainty of the results, they recommended more appropriate methods and accurate measurement of infiltration rates and quantification of the total floor plan area of the building.

The Efficiency Valuation Organization, through the International Performance of Measurement and Verification Protocol (IPMVP), defines conditions and calculation methods for determining energy savings in efficient designs [11]. The energy saving is a value that cannot be measured directly, as it refers to the energy that would be consumed with the implementation of an energy-efficient strategy. However, the previous installation would no longer exist for having its consumption measured. Thus, various estimation methods are applicable, including building computer simulation.

Therefore, in order to achieve more realistic results, one should include uncertainties in the assessment. The IPMVP [11] defines three types of uncertainties: modelling, sampling and measurement, which should be applicable to any energy efficiency project. In order to reduce uncertainty, better methods of estimation should be used, such as better measuring equipment, which adds costs to the project and should be included in the feasibility studies. The savings results should be presented in the form of intervals with a certain reliability (e.g., 95%). The only way to apply this protocol considering risk investment analysis is through the uncertainty analysis [9].

Uncertainty analysis is useful to assess building simulation models, as they are an estimation of real thermophysical phenomena. To contribute to this research field, this study aims to determine the uncertainty in thermal performance and energy consumption in a residential building generated from user behaviour and physical parameters, using computer simulation. These uncertainties are indicators of reliability of the building simulation approaches and could reveal which parameters cause most of the variation.

## 2. Method

All analyses were performed over a probabilistic approach, where the variability of output parameters (dependent variables) is determined by the uncertainty of the input parameters (independent variables). Thus, the method is organised according to Fig. 1. The computer simulations were performed using the EnergyPlus 8.0 programme.

EnergyPlus is a building simulation programme that can be used to model energy consumption, air conditioning, lighting, ventilation and other physical phenomena involving the performance of a building [12].

The steps were: (1) select the probability density functions for the parameters, (2) organize the input parameters (independent variables), (3) perform a random sampling with Latin hypercube, (4) prepare formatted input files for EnergyPlus, (5) perform uncertainty analysis and (6) perform sensitivity analysis.

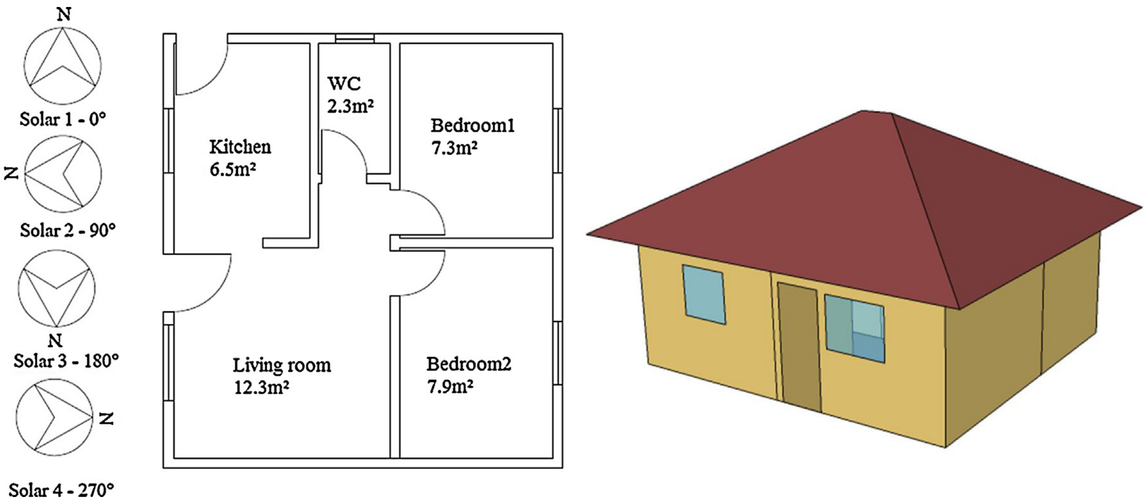



**Fig. 2.** Model used in the computer simulations, along with the solar orientation variations.

### 2.1. Computer simulation configuration

A model of a 35 $m^2$ social housing was used for all the analyses. The model can be seen in Fig. 2.

The analyses were performed for the Florianópolis climate, southern Brazil, using the Test Reference Year (TRY) weather file [13]. The constructive components adopted have shown high frequency of occurrence in this type of households in Florianópolis, i.e., walls of brickwork, asbestos cement roof and PVC ceiling.

The air conditioning system was modelled considering a COP (Coefficient of Performance) of 3.0 for the cooling coil and an efficiency of 0.70 for the fan. For heating, an auto-sized electrical resistance was considered.

It should be emphasized that actual social houses in Florianópolis are not equipped with air conditioning systems. In this work, this system was only considered for generating energy consumption with environmental conditioning and to serve as an alternative dependent variable for the analysis, other than a simple internal air temperature.

### 2.2. Dependent variables

The dependent variables chosen were the thermal performance of the building, represented by degree-hours for heating and cooling, and energy consumption for air conditioning. These dependent variables were calculated using the EnergyPlus version 8.0 programme. Independent simulations were considered for determination of the degree-hours and energy consumption.

To calculate the degree-hours for heating and cooling, the building was modelled with natural ventilation throughout the whole year.

To calculate the energy consumption for heating and cooling, the house was modelled as hybrid, i.e., with natural ventilation from 8 am to 9 pm and air conditioning from 9 pm to 8 am for the whole year. This was considered based on typical usage of air conditioning in houses in Brazil, as it is used only for sleeping purposes (in spite of decreasing temperatures at night). The same was considered for the hour of natural ventilation, in which the occupants typically leave the windows open during the day, in spite of high outside temperatures. Thus, the air conditioning was only considered in the bedrooms, and for the other rooms (kitchen, bathroom and living room) the natural ventilation was maintained.

Degree-hours for heating and cooling were calculated for each room using Eqs. (1) and (2). Figs. 3 and 4 show examples of the degree-hours calculation. Therefore, to generalize the entire building, an arithmetic average was calculated using the results of the two bedrooms, living room and kitchen, which are the long permanence rooms.

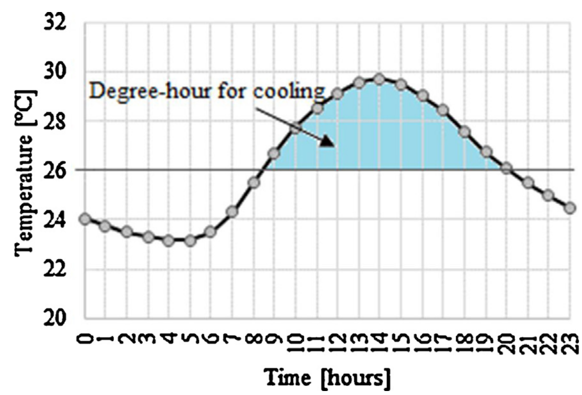



**Fig. 3.** Example of calculation of the degree-hour for cooling.

The results of individual rooms were not analysed for matters of space, as each room would result in four dependent variables (two degree-hours and two energy consumptions) and four sets of important parameters. The analysis among rooms is beyond the scope of this study.

$$\mathrm{DHH} = \sum_{i=1}^{8760} \begin{cases} \text{if } T_i < 19\ ^\circ\mathrm{C}; & 19 - T_i \\ \text{if } T_i \geq 19\ ^\circ\mathrm{C}; & 0 \end{cases} \quad (1)$$

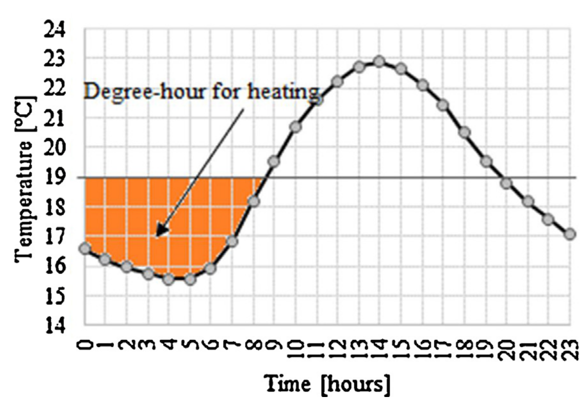



**Fig. 4.** Example of calculation of the degree-hour for heating.

**Table 1**
Simulated cases.

| Model | Uncertainty | Type of environmental conditioning | Solar orientation [°] | Number of runs |
|---|---|---|---|---|
| 1 | Physical | Natural ventilation | 0 | 120 |
| 2 | Physical | Hybrid | 0 | 120 |
| 3 | User behaviour | Natural ventilation | 0 | 140 |
| 4 | User behaviour | Hybrid | 0 | 140 |
| 5 | Physical | Natural ventilation | 90 | 120 |
| 6 | Physical | Hybrid | 90 | 120 |
| 7 | User behaviour | Natural ventilation | 90 | 140 |
| 8 | User behaviour | Hybrid | 90 | 140 |
| 9 | Physical | Natural ventilation | 180 | 120 |
| 10 | Physical | Hybrid | 180 | 120 |
| 11 | User behaviour | Natural ventilation | 180 | 140 |
| 12 | User behaviour | Hybrid | 180 | 140 |
| 13 | Physical | Natural ventilation | 270 | 120 |
| 14 | Physical | Hybrid | 270 | 120 |
| 15 | User behaviour | Natural ventilation | 270 | 140 |
| 16 | User behaviour | Hybrid | 270 | 140 |

$$\mathrm{DHC} = \sum_{i=1}^{8760} \begin{cases} \text{if} \quad T_i > 26 \quad ^\circ\mathrm{C}; & T_i - 26 \\ \text{if} \quad T_i \leq 26 \quad ^\circ\mathrm{C}; & 0 \end{cases} \tag{2}$$

where DHH is the degree-hour for heating [°C h]; DHC is the degree-hour for cooling [°C h]; $i$ is each hour of the year up to a maximum of 8760 [hour]; $T_i$ is the operative temperature in each hour of the year, for each long permanence room [°C].

The energy consumption was calculated in an annual base, in kW h/m$^2$/year. The heating temperature set point was 20 °C and the cooling temperature set point was 26 °C. These set point values are related to the thermal comfort of the occupants, whereas the limits for degree-hour of Eqs. (1) and (2) only promote a comparison between the simulated cases in this work. In other words, they do not need to be equal.

### 2.3. Stratified random sampling

Two types of uncertainties were analysed in this work: (1) physical and (2) user behaviour. The parameters associated with each type of uncertainty were propagated separately due to the large amount of second-order effects that could occur. In addition, each uncertainty comes from different data sources, and should not be mixed [3].

According to Heiselberg et al. [14], the sensitivity analysis can be divided into three types: screening, local and global sensitivity. Global methods have the advantage that all parameters are varied at the same time, taking into account the shape of the probability density function and the ranges of results distributions.

The uncertainty and global sensitivity analyses were performed using the Latin hypercube sampling, whose theoretical conception is superior to the Monte Carlo sampling method. The Latin hypercube method was successfully applied by several authors [3,8,15–17].

The Latin hypercube is a form of stratified sampling in which the sample is forced to comply with the probability distribution of the variable under analysis [18]. The probability function is divided into strata of equal probability, and the same number of points is chosen from each stratum [19].

No statistical criteria exists regarding the generated sample size, as the number of simulation runs do not depend on the number of parameters [5]. However, it is common to take figures greater than 80 [20]; other authors propose that the size should be greater than 3/2 of the number of parameters [8]. Herein, the Simlab 2.2 programme [21] was used to generate a 120 sample size for the physical parameters and a 140 sample size for user behaviour parameters.

Thus, 2080 computer simulation runs were carried out. Table 1 summarizes the simulated cases, with 16 groups that differ by type of conditioning (naturally ventilated or hybrid), type of uncertainty analysed (user behaviour or physical), and solar orientation (according to Fig. 2) to verify if any uncertainty prevails in some specific orientation.

### 2.4. Data source of the physical parameters uncertainties

The main issue about dealing with uncertainty analysis is the lack of accurate data of the variability of the parameters. Few studies deal with the determination of measurement errors or estimative of physical properties of materials. Table 2 summarizes the physical parameters considered in this work. The codes used for the probability distributions shown in Table 2 are:

a) *T*, which stands for triangular distribution, defined by lower, mode and upper values (three values);
b) *N*, which stands for normal distribution, defined by mean and standard deviation values (two values).

For the layer thicknesses of the materials, 10% uncertainty was adopted. For the specific heat and thermal conductivity of the layers of materials, the work of MacDonald [22] was taken as a basis, which considers the sum of the systematic uncertainties (differences in temperature, humidity and age of the samples) and random uncertainties (differences between measurements in same test conditions). Therefore, coefficients of variation of 19% for the thermal conductivity were adopted. For specific heat, 19% was adopted for brickwork and cement materials and 4% for the other materials. This difference concerns the porosity of the materials; cement and brickwork materials may accumulate greater amounts of moisture, which leads to differences in measurement of their thermal properties.

The uncertainty on the density of the materials was based on the Brazilian standard NBR 15220-2 [23]. This standard shows the densities by intervals of lower and upper values. Thus, the normative interval was considered as being 95% confidence in a normal probability distribution and, from it, an equivalent standard deviation was calculated using Eq. (3).

$$\sigma = \frac{x_{\text{upp}} - \bar{x}}{z_{(1-\alpha/2)}} \tag{3}$$

where $\sigma$ is the standard deviation of the population [kg/m$^3$]; $\bar{x}$ is the average value from the lower and upper values of the NBR 15220-2 [23] [kg/m$^3$]; $x_{\text{upp}}$ is the upper level of the NBR 15220-2 interval

**Table 2**
Uncertainty of physical parameters.

| Parameter | Unit | Distribution |
|---|---|---|
| Thickness of brickwork (wall) | m | $N$(0.01340;0.00134) |
| Thickness of the mortar inside face (wall) | m | $N$(0.0150;0.0015) |
| Thickness of the mortar outside face (wall) | m | $N$(0.0250;0.0025) |
| Density of the mortar (wall) | kg/m$^3$ | $N$(1950;76) |
| Density of the brickwork (wall) | kg/m$^3$ | $N$(1772;51) |
| Specific heat of the mortar (wall) | J/kg K | $N$(1000;190) |
| Specific heat of the brickwork (wall) | J/kg K | $N$(920;175) |
| Thermal conductivity of the mortar (wall) | W/m K | $N$(1.15;0.22) |
| Thermal conductivity of the brickwork (wall) | W/m K | $N$(0.70;0.13) |
| Solar absorptance (wall) | – | $N$(0.50;0.04) |
| Thickness of the asbestos (roof) | m | $N$(0.0050;0.0005) |
| Thickness of the PVC (ceiling) | m | $N$(0.0080;0.0008) |
| Density of the asbestos (roof) | kg/m$^3$ | $N$(2000;102) |
| Density of the PVC (ceiling) | kg/m$^3$ | $N$(1300;51) |
| Emissivity of the asbestos (roof) | – | $N$(0.90;0.02) |
| Emissivity of the PVC (ceiling) | – | $N$(0.90;0.02) |
| Specific heat of the asbestos (roof) | J/kg K | $N$(840;160) |
| Specific heat of the PVC (ceiling) | J/kg K | $N$(960;38) |
| Thermal conductivity of the asbestos (roof) | W/m K | $N$(0.95;0.18) |
| Thermal conductivity of the PVC (ceiling) | W/m K | $N$(0.20;0.02) |
| Solar absorptance (roof) | – | $N$(0.70;0.04) |
| Thickness of the ceramic (floor) | m | $N$(0.0080;0.0008) |
| Thickness of the concrete (floor) | m | $N$(0.080;0.008) |
| Density of the ceramic (floor) | kg/m$^3$ | $N$(1200;51) |
| Density of the concrete (floor) | kg/m$^3$ | $N$(2400;102) |
| Specific heat of the ceramic (floor) | kJ/kg K | $N$(920;175) |
| Specific heat of the concrete (floor) | kJ/kg K | $N$(1000;190) |
| Thermal conductivity of the ceramic (floor) | W/m K | $N$(0.70;0.13) |
| Thermal conductivity of the concrete (floor) | W/m K | $N$(1.75;0.33) |
| Ventilation opening area (bedrooms) | – | $N$(0.50;0.1) |
| Ventilation opening area (living room and kitchen) | – | $N$(0.50;0.1) |
| Ground temperatures (January) | °C | $N$(24.17;0.20) |
| Ground temperatures (February) | °C | $N$(24.44;0.20) |
| Ground temperatures (March) | °C | $N$(23.83;0.20) |
| Ground temperatures (April) | °C | $N$(22.93;0.20) |
| Ground temperatures (May) | °C | $N$(20.61;0.20) |
| Ground temperatures (June) | °C | $N$(18.85;0.20) |
| Ground temperatures (July) | °C | $N$(17.69;0.20) |
| Ground temperatures (August) | °C | $N$(17.37;0.20) |
| Ground temperatures (September) | °C | $N$(18.04;0.20) |
| Ground temperatures (October) | °C | $N$(19.44;0.20) |
| Ground temperatures (November) | °C | $N$(21.30;0.20) |
| Ground temperatures (December) | °C | $N$(22.99;0.20) |
| Ground reflectance | – | $T$(0.13;0.20;0.26) |
| Air flow coefficient for closed windows | kg/s m | $T$(0.00016;0.00028;0.00056) |

[kg/m$^3$]; $z_{(1-\alpha/2)}$ is inverse of the normal distribution, with 0.05 significance.

For the long wavelength emissivity of the materials, a standard deviation of 0.02 was adopted, and for the solar absorptance a standard deviation of 0.04 was adopted [22].

The ventilation opening area refers to a fraction representing the effective area available for natural ventilation ranging from 0 to 1. A value of 0.10 for the standard deviation was considered.

For the airflow coefficient through opening cracks, the work of Liddament [24] was taken as a basis for metallic window frames, with values defined as lower, mode and upper, considered in a triangular probability distribution.

For ground temperature, an uncertainty of 0.20 °C of standard deviation for each month of the year was considered, based on the TRY weather file [13].

The albedo (reflectance of the ground surface) was adopted as a triangular distribution with values ranging from 0.13 to 0.26, according to Thevenard and Haddad [25] for a not snowing land.

### *2.5. Data source of user behaviour parameters uncertainty*

According to Hopfe and Hensen [3], the user behaviour is a type of uncertainty difficult to determine, as it refers to how the building would be operated, what would be the daily occupation, how occupants behave against the usage of lighting and air conditioning systems and equipment [26].

For the determination of such data, a survey was performed in households in Florianópolis, southern Brazil, in order to find patterns of occupancy, user behaviour and equipment usage.

Altogether, more than 60 houses were surveyed and interviews were conducted with the residents. Information on occupants in each room of the house, opening doors and windows routines, and equipment and lighting usage were obtained.

Simultaneously, all electrical equipment were monitored up to one week, in order to find the power rate and the usage time. More details on this research can be found in [27,28]. Fig. 5 shows an example of the occupancy pattern for the bedrooms over summer, with 80% confidence interval and for weekdays and weekends.

Table 3 summarizes the parameters considered in the user behaviour uncertainties. It can be noticed that some parameters do not fit the "user behaviour" classification (as the number of occupants or radiant factors), but this nomenclature was chosen to ease understanding. The number of occupants in each room was considered as a discrete distribution, with 1 or 2 occupants in the bedrooms, and consequently, 2 or 4 in the living room and kitchen, with a 50% probability of occurrence of each value. In Table 3, $D$ stands for discrete distribution, defined by values for each level considered, and the probability of occurrence of each value. $T$ and $N$ stand for triangular and normal distributions, as explained in Section 2.4.

For occupancy and operation of doors and windows, daily intervals with 80% confidence were used for generating annual schedules, amounting 8760 h/year of profile size, based on the probability of occurrence of each value. Therefore, these parameters were varied stochastically, as each day of the year has a different profile. The variable units included in the sensitivity analysis are the number of hours in operation throughout the year (i.e., the time that the room is occupied, the number of hours that the windows and doors are totally open).

For lighting usage, schedules of 80% confidence were considered. The equipment usage was considered constant [27].

The radiant fraction of equipment was taken as a normal distribution with 0.5 mean [29] and standard deviation of 0.1. For luminaires, the radiant fraction was taken as a triangular distribution of probabilities from 0.74 to 0.95, according to the default values of EnergyPlus for different types of luminaires.

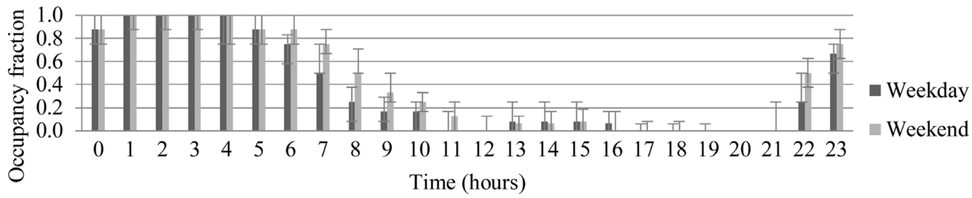



**Fig. 5.** Example of the occupancy pattern survey for the bedrooms over summer, with 80% nonparametric confidence interval.

In addition to the schedules of doors and windows operation, which were differentiated according to summer and winter, there are also uncertainties related to the temperature set point. For summer, a set point of 20 or 22 °C was taken, and for winter, 24 or 26 °C, with a 50% probability of occurrence of each value.

### 2.6. Uncertainty analysis

The uncertainty analysis aims to determine the confidence intervals for the results. For each group in Table 1 and for each dependent variable, the variability of the results by confidence intervals with the Student *t*-test was estimated. The amplitude range of the confidence interval was calculated using Eq. (4) for each dependent variable of each case simulated. The relative deviation with 95% reliability was calculated using Eq. (5).

$$\text{CI range}_i = \text{SL}_i - \text{IL}_i \quad (4)$$

$$\text{RD}_{\alpha_i} = \frac{s_i \times t_{1-\alpha/2(n-1)}}{\bar{x}_1} \times 100 \quad (5)$$

where $\text{CI range}_i$ is the amplitude or confidence interval range with 95% confidence [°C h or kW h/m$^2$ year]; $\text{SL}_i$ is the superior limit of the *i*th distribution with 95% confidence [°C h or kW h/m$^2$ year]; $\text{IL}_i$ is the inferior limit of the *i*th distribution with 95% confidence [°C h or kW h/m$^2$ year]; $\text{RD}_{\alpha_i}$ is the relative deviation with $(1-\alpha)$ confidence for the *i*th distribution [%]; $S_i$ is the standard deviation of the *i*th distribution [°C h or kW h/m$^2$ year]; $t_{1-\alpha/2(n-1)}$ is the number of deviations of the Student distribution for $(1-\alpha/2)$ confidence and $(n-1)$ degrees of freedom [non-dimensional]; $\alpha$ is the significance level equal to 0.05 [non-dimensional]; $\bar{x}_1$ is the average of the *i*th distribution [°C h or kW h/m$^2$ year].

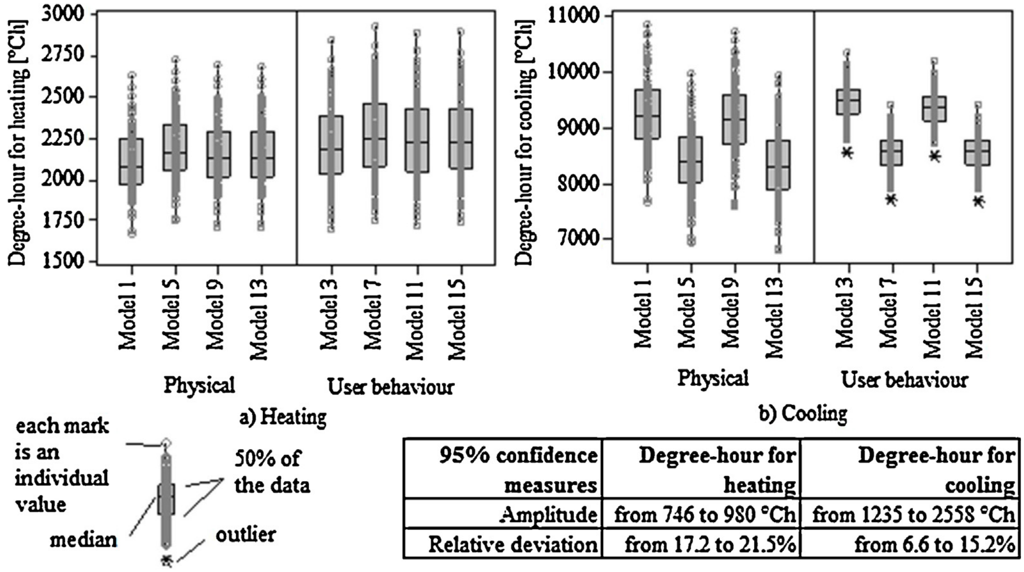
### 2.7. Sensitivity analysis

Sensitivity analysis aims to determine which parameters caused most of the results variance, i.e., the most important parameters of the experiment. The Standardised Regression Coefficient (SRC) was used, which is based on multivariate linear regression by the least square method [30]. To perform the calculation, the Simulation Environment for Uncertainty and Sensitivity Analysis (Simlab 2.2) was used, which was developed by the Joint Research Centre of European Commission [21].

The standardised regression coefficient method starts with the regression formula (Eq. (6)) and with the calculation of the $b_j$

**Table 3**
Uncertainty of parameters related to user behaviour.

| Parameter | Unit | Distribution |
|---|---|---|
| Number of occupants (bedroom) | Occupants | *D*{(1;2)(0.5; 0.5)} |
| Schedules of occupancy (bedroom) | h/year | *D*{(2684; 3229; 4009)(0.2; 0.6; 0.2)} |
| Number of occupants (living room) | Occupants | *D*{(2;4)(0.5; 0.5)} |
| Schedules of occupancy (living room) | h/year | *D*{(889; 1785; 2996)(0.2; 0.6; 0.2)} |
| Number of occupants (kitchen) | Occupants | *D*{(2; 4)(0.5; 0.5)(0.2; 0.6; 0.2)} |
| Schedules of occupancy (kitchen) | h/year | *D*{(498; 1623; 3072)(0.2; 0.6; 0.2)} |
| Average power of equipment (bedroom) | W | *D*{(90.1; 161.3; 232.5)(0.2; 0.6; 0.2)} |
| Average power of equipment (living room) | W | *D*{(146.0; 225.4; 304.6)(0.2; 0.6; 0.2)} |
| Average power of equipment (kitchen) | W | *D*{(691.5; 838.2; 984.9)(0.2; 0.6; 0.2)} |
| Average power of lighting (bedroom) | W | *D*{(25.3; 30.3; 35.3)(0.2; 0.6; 0.2)} |
| Schedules of lighting (bedroom) | h/day | *D*{(0.584; 1.167; 1.686)(0.2; 0.6; 0.2)} |
| Average power of lighting (living room) | W | *D*{(29.6; 33.7; 37.9)(0.2; 0.6; 0.2)} |
| Schedules of lighting (living room) | h/day | *D*{(1.5; 2.0; 3.2)(0.2; 0.6; 0.2)} |
| Average power of lighting (kitchen) | W | *D*{(19.0; 23.5; 28.0)(0.2; 0.6; 0.2)} |
| Schedules of lighting (kitchen) | h/day | *D*{(2.0; 3.0; 3.5)(0.2; 0.6; 0.2)} |
| Set point temperature of window over summer (bedroom) | °C | *D*{(20; 22)(0.5; 0.5)} |
| Set point temperature of window over winter (bedroom) | °C | *D*{(24; 26)(0.5; 0.5)} |
| Set point temperature of window over summer (living room) | °C | *D*{(20; 22)(0.5; 0.5)} |
| Set point temperature of window over winter (living room) | °C | *D*{(24; 26)(0.5; 0.5)} |
| Set point temperature of window over summer (kitchen) | °C | *D*{(20; 22)(0.5; 0.5)} |
| Set point temperature of window over winter (kitchen) | °C | *D*{(24; 26)(0.5; 0.5)} |
| Availability schedules operation of windows (bedroom) | h/year | *D*{(2954; 3683; 4206)(0.2; 0.6; 0.2)} |
| Availability schedules operation of windows (living room) | h/year | *D*{(1627; 2239; 2739)(0.2; 0.6; 0.2)} |
| Availability schedules operation of windows (kitchen) | h/year | *D*{(3330; 4058; 5200)(0.2; 0.6; 0.2)} |
| Availability schedules operation of doors (bedroom) | h/year | *D*{(3799; 5099; 5978)(0.2; 0.6; 0.2)} |
| Availability schedules operation of doors (living room) | h/year | *D*{(1630; 2434; 3384)(0.2; 0.6; 0.2)} |
| Availability schedules operation of doors (kitchen) | h/year | *D*{(2232; 3255; 4510)(0.2; 0.6; 0.2)} |
| Radiant factor of luminaires (bedroom) | – | *T*(0.74; 0.85; 0.95) |
| Radiant factor of luminaires (living room) | – | *T*(0.74; 0.85; 0.95) |
| Radiant factor of luminaires (kitchen) | – | *T*(0.74; 0.85; 0.95) |
| Radiant factor of equipment (bedroom) | – | *N*(0.5;0.1) |
| Radiant factor of equipment (living room) | – | *N*(0.5;0.1) |
| Radiant factor of equipment (kitchen) | – | *N*(0.5;0.1) |




| 95% confidence measures | Degree-hour for heating | Degree-hour for cooling |
|---|---|---|
| Amplitude | from 746 to 980 °Ch | from 1235 to 2558 °Ch |
| Relative deviation | from 17.2 to 21.5% | from 6.6 to 15.2% |

**Fig. 6.** Uncertainty analysis of degree-hour for heating and cooling for models under natural ventilation.

indices by the least square method. Eqs. (7) and (8) were used to perform the calculations.

$$y_i = b_0 + \sum_j b_j x_{ij} + \varepsilon_i \quad (6)$$

$$\frac{\hat{y} - \bar{y}}{s(y)} = \sum_{i=1}^{k} \mathrm{SRC}(y, x_i) \times \frac{x_i - x_i}{s(x_i)} \quad (7)$$

$$\mathrm{SRC}(y, x_i) \times b_i \frac{s(y)}{s(x_i)} \quad (8)$$

where: $y_i$ is the $i$th value of the y dependent variable [variable unit]; $b_0$ is a regression constant [non-dimensional]; $\varepsilon_i$ is the error of the regression [variable unit]; $x_{ij}$ is the ith value of each $j$ independent variable [variable unit]; $b_j$ are the coefficients of each $j$ independent variable obtained with the least square method [non-dimensional]; $\bar{y}$ is the average of $y$ [variable unit]; $\bar{x}_i$ is the average of $x_i$ [variable unit]; $S(y)$ is the standard deviation of $y$ [variable unit]; $S(x_i)$ is the standard deviation of $x_i$; $\hat{y}$ is the regression model without the error term [variable unit]; $\mathrm{SRC}(y, x_i)$ is the standardised regression coefficients of $x_i$ in $y$ [non-dimensional].

## 3. Results

This section shows the results of the uncertainty and sensitivity analyses.

### 3.1. Uncertainty analysis

Fig. 6 shows the results separated by dependent variable (degree-hour for heating and degree-hour for cooling).

For degree-hour for heating, there is no significant difference in the amplitude between models (physical, user behaviour, and solar orientation), as well as the absolute value of the median. The lower value was 1670 °C h for model 1, and the upper value was 2927 °C h for Model 7. The amplitude (confidence interval range obtained from Eq. (4)) varied from 746 to 980 °C h, and the relative deviation varied from 17.2 to 21.5% (between models).

For degree-hour for cooling, the difference between the amplitudes of the models with physical uncertainty (Models 1, 5, 9 and 13) and models with user behaviour uncertainty (Models 3, 7, 11 and 15) is clear. The uncertainty of the physical parameters is larger, from 2427 to 2558 °C h of amplitude, and for the user behaviour parameters is from 1235 to 1300 °C h.

Fig. 7 shows the results for the energy consumption with heating and cooling. An opposite tendency compared with Fig. 6 is noticed. The uncertainty of the user behaviour was greater than the physical parameter uncertainty in heating, with greater amplitude and higher medians (Models 4, 8, 12 and 16). As for cooling, the two types of uncertainties resulted in similar amplitudes.

For heating energy consumption, the amplitude ranged from 96.6 to 212.7 kW h/m$^2$ year, and the relative deviation ranged from 19.5 to 36.5%.

For cooling energy consumption, the amplitude ranged from 90.9 to 122.7 kW h/m$^2$ year, and the relative deviation ranged from 38.0 to 43.5% (the larger deviation achieved in this study). For example, if an energy-efficient strategy resulted in a 20% reduction in energy consumption with cooling through a deterministic simulation, up to 43.5% of uncertainty should be considered. Therefore, such an energy-efficient strategy would not be effective or technically feasible, as the uncertainty is higher than the reduction in energy consumption.

An observation can be made in the heating energy consumption. In models with user behaviour uncertainty, a discontinuity in the data distribution can be noticed (marked in red colour), which features two different phenomena occurring in the same distribution. This fact will be clarified in the next section.

### 3.2. Sensitivity analysis

Tables 4 and 5 show the ranking of the most influent parameters for physical uncertainties for both degree-hour and energy consumption, respectively. Tables 6 and 7 show the ranking of the most influent parameters for user behaviour uncertainties also for both degree-hour and energy consumption, respectively. Parameters are shown in decreasing order of importance, with also the Standardised Regression Coefficient and $R^2$ (coefficient of determination) interval. The higher the standardised regression coefficient (in absolute value), the higher the importance of the parameter.

The positive coefficients indicate direct proportionality with the dependent variables, and the negative, inverse proportionality. For example, by increasing the specific heat of the mortar of the walls, the degree-hour for heating decreases; whereas by increasing the solar absorptance of the roof, the degree-hour for cooling increases.

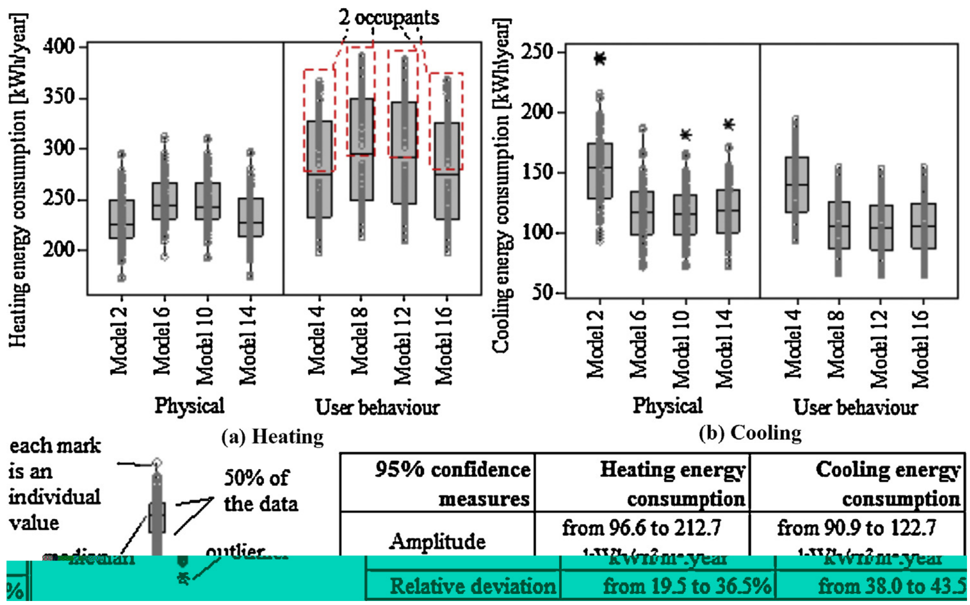



**Fig. 7.** Uncertainty analysis of heating and cooling energy consumption for models under hybrid ventilation.

Tables 4–7 show only the number of parameters needed to represent 90% of the total variance of each type of uncertainty. For physical uncertainty, 15 to 18 parameters were needed to represent 90% of the variance (Tables 4 and 5), whereas the uncertainty for user behaviour needed from 9 to 11 parameters (Tables 6 and 7).

The order of the most important parameters was the same despite the solar orientation. Therefore, in each type of uncertainty the average values of the standardised regression coefficients were calculated between models, generalizing the solar orientation.

The values of $R^2$ have close proximity to one, which indicates excellent correlation, i.e., large amount of the variance of the simulations was explained by a linear regression [7]. Thus, it is not necessary to use the rank transformation, as the standardised rank regression coefficients [30].

The uncertainty related to the specific heat of material of the walls and thickness of the materials were the most important in heating (in cold periods). In cooling energy consumption, i.e., in warm periods, the uncertainty of solar absorptance and albedo prevails among the others. Different parameters could be found for different climates, as in [3] which have found infiltration rates most important than other thermal properties, for office buildings in Netherlands. Other authors have found the thermal conductivity of insulation layers as the most important parameter for a house in Italy climate [31].

For the user behaviour parameters, the number of occupants of bedrooms, the average power with equipment in bedrooms, schedules of occupancy in kitchen and bedrooms were important parameters, in all dependent variables.

All these parameters need further attention in the steps of modelling and building simulation design. Parameters not listed, theoretically, could be set to any value within the range of variation [7], because their uncertainty would not cause significant loss of accuracy.

However, one cannot neglect the uncertainty of the parameters listed in Tables 4 and 5. There is always some uncertainty associated with these parameters, regardless the building.

**Table 4**
Sensitivity analysis of degree-hours for heating and cooling for physical uncertainty.

| Rank | Physical uncertainty (Models 1, 5, 9, 13) | | | |
|---|---|---|---|---|
| | Degree-hour for heating | | Degree-hour for cooling | |
| | Parameter | SRC | Parameter | SRC |
| 1 | Specific heat of the mortar (wall) | −0.5235 | Solar absorptance (roof) | 0.5836 |
| 2 | Specific heat of the brickwork (wall) | −0.3453 | Solar absorptance (wall) | 0.5513 |
| 3 | Solar absorptance (wall) | −0.2788 | Ground reflectance | 0.4548 |
| 4 | Ground temperatures (positive variation) | 0.2340 | Specific heat of the mortar (wall) | −0.3530 |
| 5 | Thickness of the brickwork (wall) | −0.2310 | Specific heat of the brickwork (wall) | −0.2560 |
| 6 | Solar absorptance (wall) | −0.2103 | Ground temperatures (negative variation) | 0.1321 |
| 7 | Ground reflectance | −0.1815 | Thickness of the mortar inside face (wall) | −0.1275 |
| 8 | Thickness of the mortar inside face (wall) | −0.1803 | Emissivity of the asbestos (roof) | −0.1230 |
| 9 | Specific heat of the concrete (floor) | −0.1478 | Thickness of the brickwork (wall) | −0.1223 |
| 10 | Thickness of the mortar outside face (wall) | −0.1403 | Specific heat of the concrete (floor) | −0.0850 |
| 11 | Thermal conductivity of the mortar (wall) | 0.1261 | Density of the mortar (wall) | −0.0758 |
| 12 | Emissivity of the asbestos (roof) | 0.1177 | Vent. opening area (bedrooms) | −0.0710 |
| 13 | Density of the mortar (wall) | −0.1155 | Vent. opening area (living room and kitchen) | −0.0662 |
| 14 | Thickness of the PVC (ceiling) | −0.0954 | Thermal conductivity of the concrete (floor) | −0.0644 |
| 15 | Thermal conductivity of the brickwork (wall) | 0.0838 | Thickness of the mortar inside face (wall) | −0.0637 |
| 16 | Emissivity of the PVC (ceiling) | 0.0702 | | |
| 17 | Density of the brickwork (wall) | −0.0641 | | |
| 18 | Thermal conductivity of the PVC (ceiling) | 0.0617 | | |
| $R^2$ | 0.9914–0.9918 | | 0.9973–0.9976 | |

**Table 5**
Sensitivity analysis of energy consumption with heating and cooling for physical uncertainty.

| Rank | Physical uncertainty (Models 2, 6, 10, 14) | | | |
|---|---|---|---|---|
| | Heating energy consumption | | Cooling energy consumption | |
| | Parameter | SRC | Parameter | SRC |
| 1 | Specific heat of the mortar (wall) | −0.5673 | Specific heat of the mortar (wall) | 0.5357 |
| 2 | Specific heat of the brickwork (wall) | −0.3670 | Specific heat of the brickwork (wall) | 0.3470 |
| 3 | Thickness of the brickwork (wall) | −0.2555 | Solar absorptance (wall) | 0.2760 |
| 4 | Solar absorptance (wall) | −0.1885 | Solar absorptance (roof) | 0.2475 |
| 5 | Thickness of the mortar inside face (wall) | −0.1843 | Ground reflectance | 0.2299 |
| 6 | Thickness of the mortar outside face (wall) | −0.1750 | Thickness of the brickwork (wall) | 0.2033 |
| 7 | Ground temperatures (negative variation) | 0.1735 | Thickness of the mortar inside face (wall) | 0.1848 |
| 8 | Thermal conductivity of the mortar (wall) | 0.1566 | Density of the mortar (wall) | 0.1173 |
| 9 | Thickness of the PVC (ceiling) | −0.1368 | Thickness of the mortar outside face (wall) | 0.1162 |
| 10 | Density of the mortar (wall) | −0.1240 | Ground temperatures (positive variation) | 0.0986 |
| 11 | Solar absorptance (roof) | −0.1213 | Emissivity of the asbestos (roof) | −0.0860 |
| 12 | Ground reflectance | −0.1210 | Thickness of the PVC (ceiling) | 0.0784 |
| 13 | Thermal conductivity of the brickwork (wall) | 0.1158 | Density of the brickwork (wall) | 0.0714 |
| 14 | Emissivity of the asbestos (roof) | 0.0929 | Thermal conductivity of the mortar (wall) | −0.0676 |
| 15 | Specific heat of the concrete (floor) | −0.0876 | Specific heat of the concrete (floor) | −0.0466 |
| 16 | Thermal conductivity of the PVC (ceiling) | 0.0875 | Thermal conductivity of the brickwork (wall) | −0.0463 |
| 17 | Density of the brickwork (wall) | −0.0715 | | |
| $R^2$ | 0.9911–0.9920 | | 0.9938–0.9941 | |

**Table 6**
Sensitivity analysis of degree-hours for heating and cooling for user behaviour uncertainty.

| Rank | User behaviour uncertainty (Models 3, 7, 11, 15) | | | |
|---|---|---|---|---|
| | Degree-hour for heating | | Degree-hour for cooling | |
| | Parameter | SRC | Parameter | SRC |
| 1 | Number of occupants (bedroom) | −0.7218 | Number of occupants (bedroom) | 0.5057 |
| 2 | Schedules of occupancy (kitchen) | −0.3013 | Average power of equipment (bedroom) | 0.4495 |
| 3 | Average power of equipment (bedroom) | −0.2773 | Schedules of occupancy (kitchen) | 0.3445 |
| 4 | Schedules of occupancy (living room) | −0.2478 | Average power of equipment (kitchen) | 0.3160 |
| 5 | Number of occupants (living room) | −0.2245 | Schedules of occupancy (living room) | 0.2398 |
| 6 | Schedules of occupancy (bedroom) | −0.1990 | Number of occupants (living room) | 0.2282 |
| 7 | Average power of equipment (kitchen) | −0.1745 | Schedules of occupancy (bedroom) | 0.2097 |
| 8 | Number of occupants (kitchen) | −0.1598 | Number of occupants (kitchen) | 0.2034 |
| 9 | Average power of equipment (living room) | −0.0667 | Average power of equipment (living room) | 0.1762 |
| 10 | | | Availability sch. operation of doors (kitchen) | 0.1648 |
| 11 | | | Radiant factor of equipment (bedroom) | −0.0654 |
| $R^2$ | 0.9815–0.9833 | | 0.9780–0.9798 | |

The uncertainty in the ground temperature was considered as the sum of the Standardised Regression Coefficients between the months that generated either positive or negative variation. For degree-hours for heating, the uncertainty in the ground temperature from April to October (negative variation) was the fourth most important parameter.

The influence of the uncertainty of albedo is noted, which is a parameter commonly overlooked.

In the case of heating energy consumption, for the user behaviour uncertainty, the number of occupants had great influence compared to the other parameters. This fact characterizes the discontinuity found in Fig. 7a representing two significantly

**Table 7**
Sensitivity analysis of energy consumption with heating and cooling for user behaviour uncertainty.

| Rank | User behaviour uncertainty (Models 4, 8, 12, 16) | | | |
|---|---|---|---|---|
| | Heating energy consumption | | Cooling energy consumption | |
| | Parameter | SRC | Parameter | SRC |
| 1 | Number of occupants (bedroom) | −0.9000 | Number of occupants (bedroom) | 0.3997 |
| 2 | Average power of equipment (bedroom) | −0.2443 | Average power of equipment (bedroom) | 0.2664 |
| 3 | Schedules of occupancy (bedroom) | −0.2028 | Schedules of occupancy (bedroom) | 0.0868 |
| 4 | Schedules of occupancy (living room) | −0.0917 | Radiant factor of equipment (bedroom) | −0.0704 |
| 5 | Number of occupants (living room) | −0.0850 | Number of occupants (living room) | 0.0454 |
| 6 | Avail. sch. operation of doors (bedroom) | −0.0607 | Average power of equipment (living room) | 0.0397 |
| 7 | Schedules of occupancy (kitchen) | −0.0558 | Schedules of occupancy (living room) | 0.0327 |
| 8 | Radiant factor of equipment (bedroom) | 0.0390 | Average power of equipment (kitchen) | 0.0208 |
| 9 | Average power of equipment (kitchen) | −0.0369 | Number of occupants (kitchen) | 0.0150 |
| 10 | | | Schedules of occupancy (kitchen) | 0.0126 |
| 11 | | | Average power of lighting (living room) | 0.0097 |
| $R^2$ | 0.9886–0.9954 | | 0.9887–0.9954 | |

different probability distributions: one for the simulations with two occupants in the house, and another for the simulations with four occupants.

## 4. Conclusions

This study has shown a user behaviour and physical parameters uncertainty analysis in thermal performance and energy consumption of a house in Florianópolis, southern Brazil.

The importance of considering uncertainties in the input parameters in the simulations is noticed, since the confidence intervals of the results obtained are relevant.

Up to 17.2% of uncertainty was obtained for physical parameters and 21.5% for user behaviour parameters for degree-hour for heating. For degree-hour for cooling, 15.2% of uncertainty was obtained for physical parameters, and 6.6% for user behaviour parameters.

For energy consumption, high uncertainties were achieved compared to the degree-hour variables. Up to 19.5% and 36.5% of uncertainty was obtained for physical and user behaviour parameters, respectively, for heating energy consumption. And up to 43.5% and 38.0% of uncertainty was obtained for physical and user behaviour parameters, respectively, for cooling energy consumption. All these uncertainties were determined with 95% confidence.

The quantification of the uncertainty and reliability of these simulations is more important than proposing solutions for thermal and energy performance with deterministic simulations. Such quantification could only be achieved in this paper by using different tools such as whole building simulation programmes with sensitivity analysis packages.

The method presented in this work opens the possibility of analysing risk of investment and decision making process. Thus, the probability of having success in implementing some energy-efficient strategy could be determined.

The uncertainty analysis is important to determine the minimum required accuracy in the input parameters to generate given accuracy on the dependent variable [32]. The computer tool user needs to know the influence of the accuracy of the input parameters in the model, so that effective strategies can be made with greater reliability [5].

This study serves as the basis for future standardization of computer simulations in Brazil, as the method could be replicated to other cases to find general important parameters. In this study, for the physical uncertainty analysis, the specific heat and thickness of materials, solar absorptances, ground temperatures, and the albedo need more accuracy. In the user behaviour uncertainty analysis, the occupancy schedules, the equipment power and the number of occupants need to be determined with greater attention.

These results can help in energy performance calibration studies of computer models with actual data measurement. There should not be efforts to considering parameters that do not have influence on the results, as the radiant factor of luminaires or thermal properties of the floor and ceiling materials.

As an attempt to reduce the inaccuracy, i.e., to reduce the confidence interval of the results, more accurate methods could be applied to determine the thermal properties of walls and roof materials, as well as monitoring the usage and the energy demand of the building.

A limitation of this study relies on the fact that one typology of residential building of a single city was analysed. However, the method described herein will be the subject of future studies, covering different climatic conditions of Brazil and different residential typologies.

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